Optimal investment and scheduling of distributed energy resources with uncertainty in electric vehicle driving schedules

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Abstract

The large scale penetration of electric vehicles (EVs) will introduce technical challenges to the distribution grid, but also carries the potential for vehicle-to-grid services. Namely, if available in large enough numbers, EVs can be used as a distributed energy resource (DER) and their presence can influence optimal DER investment and scheduling decisions in microgrids. In this work, a novel EV fleet aggregator model is introduced in a stochastic formulation of DER-CAM [1], an optimization tool used to address DER investment and scheduling problems. This is used to assess the impact of EV interconnections on optimal DER solutions considering uncertainty in EV driving schedules. Optimization results indicate that EVs can have a significant impact on DER investments, particularly if considering short payback periods. Furthermore, results suggest that uncertainty in driving schedules carries little significance to total energy costs, which is corroborated by results obtained using the stochastic formulation of the problem.

Keywords: microgrids, uncertainty, electric vehicles, electric storage, distributed energy resources, DER, driving patterns, microgrids, uncertainty

1. Introduction

The definition of Distributed Energy Resources (DER) expands on the definition of Distributed Generation (DG) by including both storage and controllable loads [2], [3]. It carries all the potential benefits of DG, but also considers additional load shifting and demand response measures that add to the complexity of strategic DER investment and scheduling decisions in microgrids, particularly under uncertainty. New and emerging technologies add to this problem, and plug-in electric vehicles (EV) are a clear example. A large scale penetration of EVs in microgrids will introduce new technological

challenges and add to electric loads [4], but will also carry a significant potential for ancillary services [5–7]. Under this scenario EVs will be considered a DER and must be included in DER investment decisions.

The problem of optimal DER investment and scheduling deals with finding the optimal DER configuration and dispatch under given energy loads, technology data, market information and weather conditions. Solutions provide optimal installed capacity and operation schedule of each DER, including renewable and conventional generation technologies, combined heat and power production, local energy storage of both electricity and heat, and demand response. This is typically done considering annualized capital costs, operation and maintenance costs, and fuel costs, as well as grid purchases under different tariff schemes. It is often the complexity of these tariff schemes, with high time-dependent power and energy rates that make DER investment economically attractive, although environmental motivations are also common [8]. Therefore, the objective function in DER investment and scheduling problems generally focuses on total cost minimization, but environmental and multi-objective approaches are also used.

Several studies have addressed DER investment and scheduling problems: In [9], a mixed integer linear program (MILP) is presented for structural and operational optimization of distributed energy systems, including transport of electricity, liquid fuels and water. In [10], a linear program is developed for high level design and unit commitment in a microgrid, considering explicit islanded mode periods. A MILP model, DER-CAM, is described in [1], dealing with optimal DER investment and introducing the impact of carbon taxation in optimal investment decisions. A similar model is introduced in [11], dealing with DER investments in Japan. In [12], a MILP model is presented to optimize the daily scheduling of a microgrid while introducing a diversity constraint to ensure higher reliability. The optimal design and operation of DER is also considered in [13], taking into account the design of the heating pipeline network. In [14], a genetic algorithm is used to solve the mixed integer non-linear formulation of optimal DER investment in a residential area in Beijing. The short term scheduling of DER is analyzed in [15], using signalized particle swarm optimization.

While some of these models already present a high level of sophistication and address a large number of issues in DER investment and scheduling problems, little work has been done considering EVs and vehicle-to-grid interactions (V2G) in the presence of uncertainties.

V2G is a relatively new concept and is based on the principle that if a significantly high number of EVs is available at the grid it will not only have an impact on the loads, but will also have the potential to be used as a DER. A common approach to the interface between the EVs and the grid is the use of Aggregators, so that the full V2G potential can be achieved and the EV fleet can be effectively integrated and managed [16]. Ancillary services provided by V2G can be both capacity- and energy-based, and

frequency regulation is seen as a key potential service [17]. The economic viability and business models of V2G technology have already been addressed [18–20], and models have been presented regarding EV bidding and optimal charging strategies [21]. Some work has also been focused on the problem of optimally managing a microgrid including vehicle-to-grid interactions [22], and in [23], the role of the Aggregator is addressed and a mathematical formulation is presented with respect to frequency regulation. In [24], a stochastic method is developed to optimize the use of renewable sources to charge electric vehicles. However, few studies address V2G benefits while analyzing DER investments at microgrids.

In [25], DER-CAM is used to address the investment and planning decisions of DERs in the presence of EVs as a deterministic optimization problem, while the EV fleet Aggregator model considers only a single driving schedule for the entire fleet and defines a typical year by 3 typical days of hourly loads per month.

Problem statement

The work presented in this paper advances the state-of-the-art of DER investment and scheduling problems by adding to the work presented in [25]. It addresses the problem of finding optimal DER investment options considering that privately owned EVs will become widely available at and may influence other DER investment decisions in microgrids due to their V2G potential.

In previous work this was done using a less detailed deterministic model, whereas now it is addressed by proposing a novel stochastic programming formulation of the problem with a new EV fleet aggregator model and considering uncertainty in driving schedules. In particular, an updated version of DER-CAM was created to accommodate these features, also with an increased amount of data from 3 to 7 typical days of hourly loads per month for the typical year (a total of 84 typical days per year rather than 36) to better capture potential storage benefits.

The resulting version of DER-CAM is then used to perform a case study with technology costs and performance coefficients being forecasted for 2020, when it is expected that EVs may be widely available and V2G benefits within reach. Among other settings, the problem is solved both with and without considering EVs, which allows understanding how their presence and the uncertainty in their driving schedules may influence the adoption of other technologies.

The remainder of this paper is organized as follows: Section 2 introduces briefly DER-CAM and its main versions and past applications. Section 3 describes the EV fleet aggregator model proposed in this work and Section 4 introduces the stochastic formulation of DER-CAM. Section 5 introduces the data used in the case study. Section 6 discusses the optimization runs and main results obtained. In Section 7, the main conclusions are presented.

2. DER-CAM

DER-CAM is a MILP model developed by the Lawrence Berkeley National Laboratory and used extensively to address the problem of optimally investing and scheduling DER under multiple settings. Its earliest development stages go back to 2000 [26], and stable versions can be accessed freely by the general public using a web interface [27].

Along with HOMER [28], formerly developed by the National Renewable Energy Laboratory, it is one of the few optimization tools of its kind that is available for public use. It has been continuously improved to incorporate new technologies and features, and used in several peer-reviewed publications [1], [29–31]. Recently, it has also been updated to incorporate EVs [25].

The key inputs in DER-CAM are customer loads, market tariffs including electric and natural gas prices, techno-economic data of DG technologies including capital and operation and maintenance costs, electric efficiency, heat-to-power ratio, sprint capacity, maximum operating hours, among others. Key outputs include energy costs, the optimal installed onsite capacity and dispatch of selected technologies, and demand response measures. Figure 1 presents a high level representation of the energy flows modeled in DER-CAM. The purpose of the model is to find the optimal combination of technology adoption and operation to supply the services represented on the right side of Figure 1, while optimizing the energy flows to minimize costs and / or CO_2 emissions.

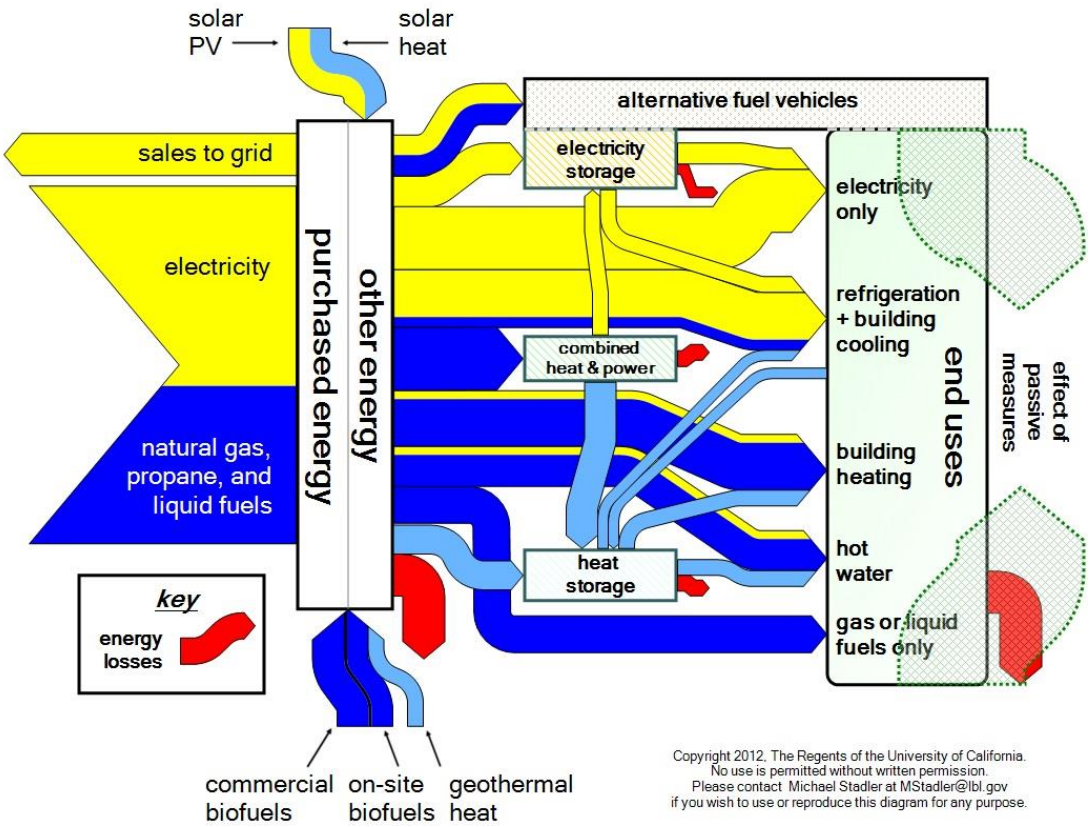

Figure 1 – High level schematic of DER-CAM

Two main versions of DER-CAM have been developed: Investment & Planning DER-CAM, available for both research and the general public, and Operations DER-CAM, available only for research purposes. Investment & Planning DER-CAM deals with the assignment problem described in section 1, and picks optimal microgrid equipment combinations based on either 36 or 84 typical days representing a year of hourly energy loads and technology costs and performance, fuel prices and utility tariffs. Operations DER-CAM deals with problem of optimal dispatch in a microgrid for a given period, typically a week ahead, with a time resolution of 5 min, 15 min, or 1 h, assuming the installed capacity is known and using weather forecasts from the web to forecast requirements.

In this paper, a new aggregated EV interconnection model is introduced for the Investment & Planning DER-CAM, and stochastic programming is implemented in the model in order to consider uncertainty in driving schedules. The model considers 84 typical day types per year.

3. EV Fleet Aggregator model

In previous work, DER-CAM considered EVs assuming a fixed driving pattern which was followed by the entire EV fleet. Thus, all vehicles were assumed to either connect or disconnect simultaneously, which is an important limitation. Additionally, the model only explicitly accounted for EV operations while they were connected to the microgrid, and home charging as well as CO_2 emissions during offsite periods were estimated using indirect calculations. That model was developed considering 3 typical days in each month, and continuity was only enforced within each day type and not between consecutive days.

The proposed model in this paper addresses all the aforementioned limitations. Now, the EV fleet can be distributed between one of four states in each time step – at the microgrid, in traffic going home, in traffic to the microgrid, and at home – and all variables concerning EV operations are calculated explicitly in each time step, which also allows forcing continuity in the state of charge (SOC) in EVs between consecutive days.

Additionally, the following assumptions were considered in the new aggregator model:

- The non-dimensional time-dependent distribution of the EV fleet between different states is known;
- Electricity used for driving is considered, but not included in microgrid energy costs;
- All cars charge enough electricity at home for an average daily roundtrip. Additional charging required for later microgrid usage is calculated by the model;

- Electricity originally meant for driving can be used while cars are at the microgrid, but if so, batteries must be recharged to a minimum SOC that guarantees the trip back home and this usage is paid by the microgrid;
- When cars change state, the SOC of these cars is equal to the average SOC of the fleet in the departing state;
- If cars transition between “Home” and “Traffic to microgrid”, the SOC of these cars is equal to the average SOC of the fleet at “Home”, plus the amount required for a daily roundtrip.
- While it is assumed other DER are owned by the microgrid owner, this is not the case with EVs. Therefore, EV costs include microgrid charging infrastructures, electricity exchange costs and battery degradation costs, but no direct EV investments are considered.

A schematic representation of the aggregator model introduced is shown in Figure 2. In this diagram, ***a*** and ***b*** represent the fleet distribution and state transition parameters, ***c*** and ***d*** are the optimum fleet size and electric input and output decisions, and ***e***, ***f***, and ***g*** are the electricity stored while parked at home or microgrid, the electricity consumed for driving and the electricity stored in traffic, respectively. It must be noted that the total EV fleet dimension is a key decision variable, as well as the electricity inputs and outputs both at home and at the microgrid. Electricity stored in each state and time step can be calculated once capacity, inputs and outputs are known. The number of cars in each state, represented by the solid rectangles, is known and given by a time-dependent discrete distribution, ***a***, as well as the share of cars transitioning between two states, ***b***. As total EV fleet capacity is determined, so are the electricity needs for driving. The electricity transferred between states is determined given total capacity and the SOC in each state and each time step. The fleet distribution over time not only determines the availability of EVs at the microgrid site, but is also required to solve home charging and discharging, as well as travelling needs and losses from self-discharge. It should also be noted that the current fleet distribution and mathematical formulation allow a future expansion of the model by adding, for example, charging options while vehicles are in transit.

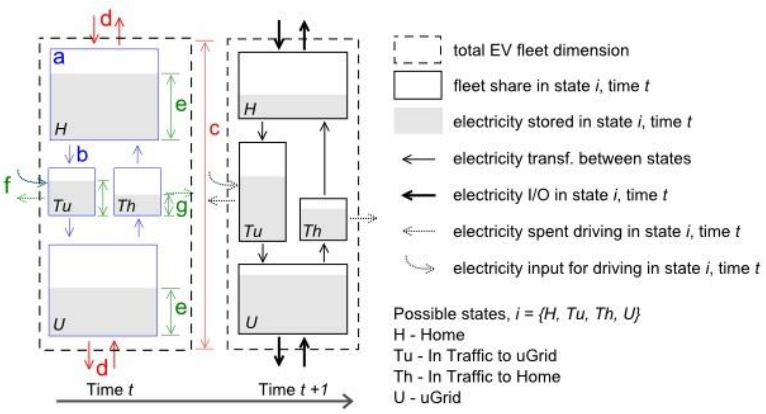

Figure 2 - EV Aggregator model schematic diagram

The detailed EV fleet aggregator mathematical formulation is described as follows:

Indices

c	set of continuous generation technologies: photovoltaic panels (PV), solar thermal panels (ST), and absorption chillers (AS)
h	hour {1,2,...,24}
k	set of storage technologies: Electric Vehicles (EV), stationary storage (ES), and thermal storage (TH)
m	month {1,2,...,12}
t	day type {1,2,...7}
u	end-use: electricity only (eo), cooling (cl), refrigeration (rf), space heating (sh), water heating (wh), natural gas only (ng)
ω	scenario {1,2,...,Ω}

Fleet distribution parameters

$EVH_{\omega,m,t,h}$	share of total EV fleet that is at home in scenario ω, month m, day type t, and during hour h
$EVTU_{\omega,m,t,h}$	share of total EV fleet that is in traffic towards the microgrid in scenario ω, month m, day type t, and during hour h
$EVU_{\omega,m,t,h}$	share of total EV fleet that is at the micro-grid in scenario ω, month m, day type t, and during hour h
$EVTH_{\omega,m,t,h}$	share of total EV fleet that is in traffic towards home in scenario ω, month m, day type t, and during hour h
$EVT2H_{\omega,m,t,h}$	share of total EV fleet that arrived home from traffic in scenario ω, month m, day type t, and during hour h
$EVH2T_{\omega,m,t,h}$	share of total EV fleet that left home to traffic in scenario ω, month m, day type t, and during hour h
$EVT2U_{\omega,m,t,h}$	share of total EV fleet that arrived the micro-grid from traffic in scenario ω, month m, day type t, and during hour h
$EVU2T_{\omega,m,t,h}$	share of total EV fleet that left the micro-grid to traffic in scenario ω, month m, day type t, and during hour h

In order to ensure continuity the following conditions are imposed to the fleet distribution parameters:

$$EVH_{\omega,m,t,h} = EVH_{\omega,m,t,h-1} + EVT2H_{\omega,m,t,h} - EVH2T_{\omega,m,t,h} \quad \forall\, \omega, m, t, h \tag{1}$$

$$EVTU_{\omega,m,t,h} = EVTU_{\omega,m,t,h-1} + EVH2T_{\omega,m,t,h} - EVT2U_{\omega,m,t,h} \quad \forall\, \omega, m, t, h \tag{2}$$

$$EVTH_{\omega,m,t,h} = EVTH_{\omega,m,t,h-1} + EVU2T_{\omega,m,t,h} - EVT2H_{\omega,m,t,h} \quad \forall\, \omega, m, t, h \tag{3}$$

$$EVU_{\omega,m,t,h} = EVU_{\omega,m,t,h-1} + EVT2U_{\omega,m,t,h} - EVU2T_{\omega,m,t,h} \quad \forall\, \omega, m, t, h \tag{4}$$

These equations state that in any given scenario, month and day type, the share of EVs in one state in hour *h* is equal to the share of EVs in that state in hour *h-1*, added with the share of cars that arrived to that state and subtracted with the share of cars that left.

Storage parameters

EVBat	average storage capacity per car (kWh)

EVDC	electricity consumed for driving per car and per hour (kWh)
PSCar	parking space required per EV (m^2)
SCRate_k	maximum charge rate of storage technology k
$\mathrm{SDCRate}_k$	maximum discharge rate of storage technology k
$\overline{\mathrm{SOC}_k}$	maximum state of charge of storage technology k
$\underline{\mathrm{SOC}_k}$	minimum state of charge of storage technology k
TotPS	total available parking space for EVs (m^2)
φ_k	losses due to self-discharge in storage technology k

Decision Variables

$cap_{(c,k)}$	installed capacity of continuous generation technology c or storage technology k (kW or kWh)
$ebioevh_{\omega,m,t,h}$	binary charge/discharge decision for EVs at home in scenario ω, month m, day type t, and during hour h
$ebiou_{\omega,k,m,t,h}$	binary charge/discharge decision at the microgrid in scenario ω, storage technology k, month m, day type t, and during hour h
$eievh_{\omega,m,t,h}$	electricity input to EVs at home in scenario ω, month m, day type t, and during hour h (kWh)
$eoevh_{\omega,m,t,h}$	electricity output from EVs at home in scenario ω, month m, day type t, and during hour h (kWh)
$esevh_{\omega,m,t,h}$	electricity stored in EVs at home in scenario ω, month m, day type t, and during hour h (kWh)
$esevtu_{\omega,m,t,h}$	electricity stored in EVs in traffic towards the microgrid in scenario ω, month m, day type t, and during hour h (kWh)
$esevth_{\omega,m,t,h}$	electricity stored in EVs in traffic towards home in scenario ω, month m, day type t, and during hour h (kWh)
$esevu_{\omega,m,t,h}$	electricity stored in EVs at microgrid in scenario ω, month m, day type t, and during hour h (kWh)
$SInput_{\omega,k,m,t,h}$	energy input from the microgrid in scenario ω, to storage technology k, , month m, day type t, and during hour h (kWh)
$SOutput_{\omega,k,m,t,h,u}$	energy output to the microgrid in scenario ω, from storage technology k, month m, day type t, and during hour h for end use u (kWh)

EV Aggregator Constraints

$$esevh_{\omega,m,t,h} = \left(esevh_{\omega,m,t,h-1}\cdot\left(1-\frac{\mathrm{EVH2T}_{\omega,m,t,h}}{\mathrm{EVH}_{\omega,m,t,h-1}}\right)+esevth_{\omega,m,t,h-1}\cdot\frac{\mathrm{EVT2H}_{\omega,m,t,h}}{\mathrm{EVTH}_{\omega,m,t,h-1}}\right)\cdot(1-\varphi_k)+eievh_{\omega,m,t,h} - eoevh_{\omega,m,t,h} \quad \forall\,\omega,m,t,h : k=\{\mathrm{EV}\} \tag{5}$$

$$esevth_{\omega,m,t,h} = \left(esevth_{\omega,m,t,h-1}\cdot\left(1-\frac{\mathrm{EVT2H}_{\omega,m,t,h}}{\mathrm{EVTH}_{\omega,m,t,h-1}}\right)+esevu_{\omega,m,t,h-1}\cdot\frac{\mathrm{EVU2T}_{\omega,m,t,h}}{\mathrm{EVU}_{\omega,m,t,h-1}}\right)\cdot(1-\varphi_k) - \mathrm{EVT2H}_{\omega,m,t,h}\cdot\frac{cap_k}{\mathrm{EVBat}}\cdot\mathrm{EVDC} \quad \forall\,\omega,m,t,h : k=\{\mathrm{EV}\} \tag{6}$$

$$esevtu_{\omega,m,t,h} = \left(esevtu_{\omega,m,t,h-1}\cdot\left(1-\frac{\mathrm{EVT2U}_{\omega,m,t,h}}{\mathrm{EVTU}_{\omega,m,t,h-1}}\right)+esevh_{\omega,m,t,h-1}\cdot\frac{\mathrm{EVH2T}_{\omega,m,t,h}}{\mathrm{EVH}_{\omega,m,t,h-1}}\right)\cdot(1-\varphi_k) + \left(\sum_h\left(\mathrm{EVTU}_{\omega,m,t,h}+\mathrm{EVTH}_{\omega,m,t,h}\right)\cdot\frac{\mathrm{EVH2T}_{\omega,m,t,h}}{\sum_h \mathrm{EVH2T}_{\omega,m,t,h}}-\mathrm{EVT2U}_{\omega,m,t,h}\right)\cdot\frac{cap_k}{\mathrm{EVBat}}\cdot\mathrm{EVDC} \quad \forall\,\omega,m,t,h : k=\{\mathrm{EV}\} \tag{7}$$

$$esevu_{\omega,m,t,h} = \left(esevu_{\omega,m,t,h-1} \cdot \left(1 - \frac{EVU2T_{\omega,m,t,h}}{EVU_{\omega,m,t,h-1}}\right) + esevtu_{\omega,m,t,h-1} \cdot \frac{EVT2U_{m,t,h}}{EVTU_{m,t,h-1}}\right) \cdot (1 - \varphi_k) + SInput_{\omega,k,m,t,h} - \sum_u SOutput_{\omega,k,m,t,h,u} \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{8}$$

$$EVH_{\omega,m,t,h} \cdot \underline{SOC_k} \cdot cap_k \leq esevh_{\omega,m,t,h} \leq EVH_{\omega,m,t,h} \cdot \overline{SOC_k} \cdot cap_k \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{9}$$

$$EVTU_{\omega,m,t,h} \cdot \underline{SOC_k} \cdot cap_k \leq esevtu_{\omega,m,t,h} \leq EVTU_{\omega,m,t,h} \cdot \overline{SOC_k} \cdot cap_k \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{10}$$

$$EVTH_{\omega,m,t,h} \cdot \underline{SOC_k} \cdot cap_k \leq esevth_{\omega,m,t,h} \leq EVTH_{\omega,m,t,h} \cdot \overline{SOC_k} \cdot cap_k \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{11}$$

$$EVU_{\omega,m,t,h} \cdot \underline{SOC_k} \cdot cap_k \leq esevu_{\omega,m,t,h} \leq EVU_{\omega,m,t,h} \cdot \overline{SOC_k} \cdot cap_k \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{12}$$

$$eievh_{\omega,m,t,h} \leq EVH_{\omega,m,t,h} \cdot cap_k \cdot SCRate_k \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{13}$$

$$eoevh_{\omega,m,t,h} \leq EVH_{\omega,m,t,h} \cdot cap_k \cdot SDCRate_k \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{14}$$

$$SInput_{k,\omega,m,t,h} \leq EVU_{\omega,m,t,h} \cdot cap_k \cdot SCRate_k \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{15}$$

$$\sum_u SOutput_{k,\omega,m,t,h,u} \leq EVU_{\omega,m,t,h} \cdot cap_k \cdot SDCRate_k \;\; \forall\, \omega, m, t, h : k = \{EV\} \tag{16}$$

$$eievh_{\omega,m,t,h} \leq ebioevh_{\omega,m,t,h} * \mathbf{M} \;\; \forall\, \omega, m, t, h \tag{17}$$

$$eoevh_{\omega,m,t,h} \leq \left(1 - ebioevh_{\omega,m,t,h}\right) * \mathbf{M} \;\; \forall\, \omega, m, t, h \tag{18}$$

$$SInput_{\omega,k,m,t,h} \leq ebiou_{\omega,k,m,t,h} * \mathbf{M} \;\; \forall\, \omega, k, m, t, h \tag{19}$$

$$\sum_u SOutput_{\omega,k,m,t,h,u} \leq \left(1 - ebiou_{\omega,k,m,t,h}\right) * \mathbf{M} \;\; \forall\, \omega, k, m, t, h, u \tag{20}$$

$$SOutput_{\omega,k,m,t,h,u} = 0 \;\; \forall\, \omega, m, t, h : k = \{EV\} \wedge u = \{sh, wh, ng\} \tag{21}$$

$$Cap_k \leq \frac{TotPS}{PSCar} \cdot EVBat \;\; : k = \{EV\} \tag{22}$$

In this model, Eqs. (5) - (8) describe how energy is transferred between different states, including all charging and discharging decisions both at home and at the microgrid. Specifically, Eqs. (5) and (8) state that in each scenario, month and day type, the electricity in cars in hour *h* is equal to the electricity in cars that were already in that state in hour *h-1*, minus the electricity in cars that went into traffic, plus the electricity in cars that arrived from traffic, plus the electricity from charging at home, minus the electricity from discharging at home during that hour, minus the electricity from self-discharging. Eqs. (6) and (7) are similar, except they consider electricity needed to meet driving demands and at this point no charging or discharging is possible, although this will be implemented in a near future to model possible charging while in transit.

The maximum and minimum state of charge conditions are imposed by Eqs. (9) - (12), by stating that the electricity stored in a given state can never be under the minimum SOC or above the maximum SOC, while Eqs. (13) - (16) set the maximum and minimum charge and discharge rates. Eqs. (17) - (20) ensure that charging and discharging cannot occur simultaneously, using binary variables and an arbitrary large quantity, **M**, to force either charge or discharge in a single time step, and Eq. (21) ensures that EVs can only be used for electricity purposes. Finally, Eq. (22) sets the maximum capacity of EVs allowed in the microgrid according to the available parking space and average battery size.

4. Stochastic DER-CAM formulation

To date, only deterministic methods had been implemented in the Investment and Planning version of DER-CAM. In this work, a stochastic formulation was implemented, already taking into account the EV fleet aggregator model described in the previous section. The nomenclature used follows previous descriptions of the DER-CAM formulation [1]. Given the nature of DER-CAM, the stochastic formulation implemented and presented here is valid for the full economic objective function of the model, although the actual formulation and model options are adapted to each case study. For instance, in the work presented here no electricity sales were considered, thus the corresponding equations and variables presented below were disabled or forced to zero.

A simplified version of the algorithm is presented in Figure 3, representing the key objective function that defines the overall strategy followed by the model, as well as the key constrains.

```
MINIMIZE:
   Total energy costs:
       energy purchase cost
       + amortized DER technology capital cost
       + annual O&M cost
SUBJECT TO:
   Energy balance:
       energy purchased + energy generated exceeds demand
   Operational constrains:
       generators, etc, must operate within installed limits
       heat recovered is limited by generated waste heat
   Regulatory constrains:
       minimum efficiency requirements
       maximum emission limits
   Investment constrains:
       maximum payback
   Storage constrains:
       electricity stored is limited by battery size
       heat storage is limited by battery size
```

Figure 3 – Representative Mixed Integer Linear Program solved by DER-CAM

In the DER models used in DER-CAM, capacity variables for different technologies can be either discrete or continuous, depending on the governing economics and available market sizes. If a technology is available in small enough modules and if capital costs and economies of scale can be described by a fixed and variable term, the optimal installed capacity of that technology is modeled as continuous variable, which contributes significantly to the computation speed of DER-CAM. Otherwise, if modules are only available in large predetermined sizes, DER installed capacities are modeled as discrete variables. This distinction can be found in the formulation below.

Indices

g	set of discrete generation technologies: internal combustion engines (ICE), micro-turbines (MT), gas turbines (GT), and fuel cells (FC)
i	set of all technologies $(j \cup k)$
j	set of all generation technologies $(g \cup c)$
n	hours previous to the current hour {0, 1, …, h}
p	period {on-peak, mid-peak, off-peak}
r	demand response type {low, med, high}
s	season {winter, summer}

Customer loads

$Cload_{m,t,h,u}$	customer load in kW in month m, day type t, during hour h and for end-use u

Market data

$CTax$	tax on carbon emissions, $/kg
$DRPrice_{(r,u)}$	cost of demand response measure of type r and end-use u, $/kWh
$EVEEP$	price of electric vehicle electricity exchange at home, $/kWh
$MktMCRate_{m,h}$	marginal carbon emissions from marketplace generation in month m and hour h, kg/kWh
$NGBSF_m$	basic service fee for natural gas in month m, $
$NGCRate$	carbon emissions rate from generation technology j, kg/kWh
$NGPrice_m$	price of natural gas in month m, $/kWh
$RTCCharge_m$	regulated tariff customer charge in month m, $
$RTCDCharge_m$	regulated tariff charge for power demand occurring during utility system peak hour during month m, $/kW
$RTEExport_{m,t,h}$	regulated tariff for electricity export in month m, day type t, during hour h, $/kWh
$RTEnergy_{m,t,h}$	regulated tariff for electricity purchase in month m, day type t, during hour h, $/kWh
$RTFCharge_m$	regulated tariff facilities charge in month m, $/kW
$RTPower_{s,p}$	regulated noncoincident demand charge under the default tariff for season s and period p, $/kW
$RTSCharge_m$	regulated tariff stand-by charge in month m, $/kW

Technology data

$Annuity_i$	annualized capital cost of DER technology i, $
$CFixcost_{(c,k)}$	fixed capital cost of DER technology modeled as continuous, $
$COPa$	absorption chillers coefficient of performance
$COPu$	central microgrid chillers coefficient of performance
$CVarcost_{(c,k)}$	variable capital cost of DER technology modeled as continuous, $/kW

$DERmaxp_g$	nameplate power rating of discrete generation technology g, kW
$DERlifetime_i$	expected lifetime of technology i, a
$DERcapcost_j$	turnkey capital cost of generation technology j, $/kW
$DEROMfix_i$	fixed annual operation and maintenance costs of technology i, $/kW
$DEROMvar_i$	variable operation and maintenance costs of technology i, $/kWh
$DERhours_j$	maximum number of hours generation technology j is permitted to operate during the year, h
$DERCostkWh_{j,m}$	production cost of technology j during month m, $/kWh
EVCL	capacity loss in electric vehicle batteries per normalized wh
EVFRC	future replacement cost of electric vehicle batteries, $/kW
S(j)	set of end-uses that can be met by technology j, $/kW
$ScEff_{c,m,h}$	solar radiation conversion efficiency of continuous generation technology c, in month m, and hour h
$SCEff_k$	charging efficiency of storage technology k
$ScPeakEff_c$	theoretical peak solar conversion efficiency of continuous generation technology c
$SDEeff_k$	discharging efficiency of storage technology k
α_j	amount of useful heat (in kW) that can be recovered from unit kW of electricity generated by technology i
η_j	electrical efficiency of generation technology j

Other parameters

BAUCost	total energy costs in the business-as-usual case, obtained by running the model with DER investments disabled
h(m)	hour in month m when utility peak occurs
IntRate	interest rate on DER investments, %
PBPeriod	maximum payback period allowed on the integrated DER investment decision
Pr_ω	probability of scenario ω occurring
ScArea	available area for solar technologies (m^2)
$Solar_{m,h}$	average fraction of maximum solar insolation received (%), during hour h of month m
t(m)	day type in month m when utility peak occurs
β_u	amount of heat (kW) generated from unit kW of natural gas purchased for end-use u

Decision Variables

$Aload_{\omega,m,t,h}$	amount of heat used to drive absorption chillers in scenario ω, month m, day type t, and during hour h, kW
$CDRLoad_{\omega,r,m,t,h,u}$	customer load not met in scenario ω due to demand response of type r, during month m, day type t, and during hour h during hour h, for end-use u costumer loads, kW
$GenU_{\omega,j,m,t,h,u}$	energy generated in scenario ω by technology j, in month m, day type t, and during hour h to meet end-use u customer loads, kW
$GenS_{\omega,j,m,t,h}$	energy generated to export in scenario ω by technology j, in month m, day type t, and during hour h, kW
$InvGen_g$	number of units of discrete generation technology g installed by the customer
$NGP_{\omega,m,t,h}$	natural gas purchase in scenario ω, month m, day type t, and during hour h
$psb_{\omega,m,t,h}$	binary decision of purchasing or selling electricity in scenario ω, month m, day type t, and during hour h, kW

$Pur_{(c,k)}$	customer purchase binary decision of continuous generation technology c, or storage technology k
$RecHeat_{\omega,j,m,t,h}$	amount of useful heat recovered in scenario ω from power generated by technology j, in month m, day type t, and during hour h, kW
$URLoad_{\omega,m,t,h,u}$	electricity purchased from distribution utility company in scenario ω, month m, day type t, and during hour h to meet end-use u costumer loads, kW

Economic objective function

$$
\begin{aligned}
\min C = & \sum_{m} \mathrm{RTCCharge}_{m} + \sum_{m} \mathrm{RTFCharge} \cdot \max\left(\sum_{u \in eo,cl,rf} \mathrm{Cload}_{m,t,h,u}\right) \\
& + \sum_{g} \mathrm{RTSCharge} \cdot InvGen_{g} \cdot \mathrm{DERmaxp}_{g} \\
& + \sum_{\omega}\sum_{m}\sum_{t}\sum_{h}\sum_{u} \mathrm{Pr}_{\omega} \cdot URLoad_{\omega,m,t,h,u} \cdot \left(\mathrm{RTEnergy}_{m,t,h} + \mathrm{CTax} \cdot \mathrm{MktMCRate}_{m,h}\right) \\
& + \sum_{\omega}\sum_{m}\sum_{u \in eo,cl,rf} \mathrm{Pr}_{\omega} \cdot \mathrm{RTCDCharge}_{m} \cdot URLoad_{\omega,m,t(m),h(m),u} \\
& + \sum_{\omega}\sum_{s}\sum_{m \in s}\sum_{p} \mathrm{Pr}_{\omega} \cdot \mathrm{RTPower}_{s,p} \cdot \max\left(\sum_{u \in eo,cl,rf} URLoad_{\omega,m,(t,h) \in p,u}\right) \\
& + \sum_{\omega}\sum_{j}\sum_{m}\sum_{t}\sum_{h} \mathrm{Pr}_{\omega} \cdot \left(GenS_{\omega,j,m,t,h} + \sum_{u} GenU_{\omega,j,m,t,h,u}\right) \cdot \left(\mathrm{DERCostkWh}_{j,m} + \mathrm{DEROMvar}_{j}\right) \\
& + \sum_{\omega}\sum_{g}\sum_{m}\sum_{t}\sum_{h} \mathrm{Pr}_{\omega} \cdot \left(GenS_{\omega,g,m,t,h} + \sum_{u} GenU_{\omega,g,m,t,h,u}\right) \cdot \frac{\mathrm{NGCRate}}{\eta_{j}} \cdot \mathrm{CTax} \\
& + \sum_{g} InvGen_{g} \cdot \mathrm{DERmaxp}_{g} \cdot \left(\mathrm{DERcapcost}_{g} \cdot \mathrm{AnnuityF}_{g} + \mathrm{DEROMFix}_{g}\right) \\
& + \sum_{i \in c,k} \left(\mathrm{CFixcost}_{i} \cdot Pur_{i} + \mathrm{CVarcost}_{i} \cdot Cap_{i}\right) \cdot \left(\mathrm{AnnuityF}_{i} + \mathrm{DEROMFix}_{i}\right) \\
& + \sum_{m} \mathrm{NGBSF}_{m} \\
& + \sum_{\omega}\sum_{m}\sum_{t}\sum_{h}\sum_{u} \mathrm{Pr}_{\omega} \cdot NGP_{\omega,m,t,h,u} \cdot \left(\mathrm{NGPrice}_{m} + \mathrm{CTax} \cdot \mathrm{NGCRate}\right) \\
& + \sum_{\omega}\sum_{r}\sum_{m}\sum_{t}\sum_{h}\sum_{u} \mathrm{Pr}_{\omega} \cdot CDRload_{\omega,r,m,t,h,u} \cdot \mathrm{DRPrice}_{r,u} \\
& + \sum_{\omega}\sum_{m}\sum_{t}\sum_{h} \mathrm{Pr}_{\omega} \cdot \mathrm{EVCL} \cdot \mathrm{EVFRC} \\
& \cdot \left(SInput_{\omega,k=\{EV\},m,t,h} + SOutput_{\omega,k=\{EV\},m,t,h} + eievh_{\omega,m,t,h} + eoevh_{\omega,m,t,h}\right) \\
& + \sum_{\omega}\sum_{m}\sum_{t}\sum_{h} \mathrm{Pr}_{\omega} \cdot \left(\frac{eievh_{\omega,m,t,h}}{\mathrm{SCEff}_{k=\{EV\}}} - eoevh_{\omega,m,t,h} \cdot \mathrm{SDEff}_{k=\{EV\}}\right) \cdot \left(\mathrm{EVEEP} + \mathrm{CTax} \cdot \mathrm{MktMCRate}_{m,h}\right) \\
& - \sum_{\omega}\sum_{j}\sum_{m}\sum_{t}\sum_{h} \mathrm{Pr}_{\omega} \cdot GenS_{\omega,j,m,t,h} \cdot \mathrm{RTEExport}_{m,t,h}
\end{aligned}
\tag{23}
$$

Microgrid constraints

$$\mathrm{Cload}_{m,t,h,u} - \sum_{r} CDRload_{\omega,r,m,t,h,u} + \sum_{k\in\{EV,ST\}} \frac{SInput_{\omega,k,m,t,h}}{\mathrm{SCEff}_k} = \sum_{j} GenU_{\omega,j,m,t,h,u} + URLoad_{\omega,m,t,h,u} + \sum_{k\in\{EV,ST\}} SOutput_{\omega,k,m,t,h,u=\{eo\}} \cdot \mathrm{SDEff}_k \quad \forall\, \omega, m, t, h : u = \{eo\} \tag{24}$$

$$\mathrm{Cload}_{m,t,h,u} - \sum_{r} CDRload_{\omega,r,m,t,h,u} + \frac{SInput_{\omega,k,m,t,h}}{\mathrm{SCEff}_k} + Aload_{\omega,m,t,h} = \sum_{j} GenU_{\omega,j,m,t,h,u} + SOutput_{\omega,k,m,t,h,u} \cdot \mathrm{SDEff}_k + \beta_u \cdot NGP_{\omega,m,t,h,u} + \sum_{g} RecHeat_{\omega,g,m,t,h,u} \quad \forall\, \omega, m, t, h : k = \{TH\} \wedge u \in \{sh, wh\} \tag{25}$$

$$\mathrm{Cload}_{m,t,h,u} = GenU_{\omega,j,m,t,h,u} + URLoad_{\omega,m,t,h,u} \cdot \mathrm{COPu} \quad \forall\, \omega, m, t, h : u \in \{cl, rf\} \tag{26}$$

$$\mathrm{Cload}_{m,t,h,u} = NGP_{\omega,m,t,h,u} \quad \forall\, \omega, m, t, h : u = \{ng\} \tag{27}$$

$$\sum_{u} GenU_{\omega,g,m,t,h,u} + GenS_{\omega,g,m,t,h} \le InvGen_g \cdot \mathrm{DERmaxp}_g \quad \forall\, \omega, g, m, t, h \tag{28}$$

$$Cap_i \le Pur_i \cdot \mathbf{M} \quad \forall\, i \in \{c, k\} \tag{29}$$

$$\sum_{u} GenU_{\omega,c,m,t,h,u} + GenS_{\omega,c,m,t,h} \le Cap_c \cdot \frac{\mathrm{ScEff}_{c,m,h}}{\mathrm{ScPeakEff}_c} \cdot \mathrm{Solar}_{m,h} \quad \forall\, \omega, m, t, h : c \in \{PV, ST\} \tag{30}$$

$$\sum_{c} \frac{Cap_c}{\mathrm{ScPeakEff}_c} \le \mathrm{ScArea} : c \in \{PV, ST\} \tag{31}$$

$$Cap_k \cdot \underline{\mathrm{SOC}_k} \le \sum_{n=0}^{h} \left(SInput_{\omega,k,m,t,n} - \sum_{u} SOutput_{\omega,k,m,t,n,u} \right) \cdot (1-\varphi_k)^{h-n} \le Cap_k \cdot \overline{\mathrm{SOC}_k} \quad \forall\, \omega, k, m, t, h \tag{32}$$

$$SInput_{\omega,k,m,t,h} \le Cap_k \cdot \mathrm{SCRate}_k \quad \forall\, \omega, k, m, t, h \tag{33}$$

$$SOutput_{\omega,k,m,t,h} \le Cap_k \cdot \mathrm{SDCRate}_k \quad \forall\, \omega, k, m, t, h \tag{34}$$

$$GenU_{\omega,j,m,t,h,u} = Aload_{\omega,m,t,h} \cdot \mathrm{COPa} \quad \forall\, \omega, m, t, h : j = \{AC\} \wedge u = \{cl, rf\} \tag{35}$$

$$\sum_{m}\sum_{t}\sum_{h}\left(\sum_{u} GenU_{\omega,g,m,t,h,u} + GenS_{\omega,g,m,t,h}\right) \le InvGen_g \cdot \mathrm{DERmaxp}_g \cdot \mathrm{DERhours}_g \quad \forall\, \omega, g, m, t, h \tag{36}$$

$$\sum_{u} RecHeat_{\omega,g,m,t,h,u} \le \alpha_g \cdot \left(\sum_{u} GenU_{\omega,g,m,t,h,u} + GenS_{\omega,g,m,t,h}\right) \quad \forall\, \omega, g, m, t, h \tag{37}$$

$$\sum_{u} URLoad_{\omega,m,t,h,u} \le psb_{\omega,m,t,h} \cdot \mathbf{M} \quad \forall\, \omega, m, t, h : u = \{eo, cl, rf\} \tag{38}$$

$$GenS_{\omega,j,m,t,h} \le \left(1 - psb_{\omega,m,t,h}\right) \cdot \mathbf{M} \quad \forall\, \omega, j, m, t, h \tag{39}$$

$$\mathrm{AnnuityF_i} = \frac{\mathrm{IntRate}}{\left(1 - \frac{1}{(1+\mathrm{IntRate})^{\mathrm{DERLifetime_i}}}\right)} \ \forall\ \mathrm{i} \tag{40}$$

$$\begin{aligned} \mathrm{C} &\leq \mathrm{BAUCost} + \sum_{g} InvGen_g \cdot \mathrm{DERmaxp_g} \cdot \mathrm{DERcapcost_g} \cdot \mathrm{AnnuityF_g} \\ &+ \sum_{i \in c,k} (\mathrm{CFixcost_i} \cdot Pur_i + \mathrm{CVarcost_i} \cdot Cap_i) \cdot \mathrm{AnnuityF_i} \\ &- \frac{\sum_g InvGen_g \cdot \mathrm{DERmaxp_g} \cdot \mathrm{DERcapcost_g} + \sum_{i \in c,k} (\mathrm{CFixcost_i} \cdot Pur_i + \mathrm{CVarcost_i} \cdot Cap_i)}{\mathrm{PBPeriod}} \end{aligned} \tag{41}$$

$$RecHeat_{\omega,j,m,t,h,u} = 0\ \forall\ \omega, j, m, t, h : u \notin S(j) \tag{42}$$

$$GenU_{\omega,j,m,t,h,u} = 0\ \forall\ \omega, g, m, t, h : j \neq \{ST\} \wedge u \in \{sh, wh, ng\} \tag{43}$$

$$GenS_{\omega,c=\{ST\},m,t,h} = 0\ \forall\ \omega, m, t, h \tag{44}$$

$$URLoad_{\omega,m,t,h,u} = 0\ \forall\ \omega, m, t, h : u \in \{sh, wh, ng\} \tag{45}$$

In this formulation, Equation (23) is the economic objective function that states that the microgrid will try to minimize total energy costs, consisting of facilities and customer charges, monthly power demand charges, time of use power demand charges, time of use energy charges inclusive of carbon taxation, costs of demand response measures and revenue from electricity sales. In addition, the objective function also considers on-site generation fuel and O&M costs, carbon taxation on on-site generation, and annualized DER investment costs. Finally, natural gas used to meet heating loads directly incurs variable and fixed costs (inclusive of carbon taxation).

The constraints to this problem are expressed in Eqs. (24) - (45):

- Eqs. (24) - (27) enforce energy balances for different end-uses. In Eq. (24), for instance, it is stated that electricity loads, minus the load not met due to demand response measures plus the electricity needed to charge storage technologies must equal the utility purchase, plus the electricity generated for local consumption, and the output of electricity storage technologies. Eq. (25) is a similar equation for heat balance, but also considers heat recovery from CHP units and heat needs to drive absorption chillers, while Eqs. (25) and (26) are specific equations for cooling and natural-gas loads;
- Eq. (28) enforces the on-site generating capacity constrain by stating that the sum of energy generated for local consumption and sale are limited to the installed capacity;
- Eq. (29) ensures that the adopted capacity of continuous technologies is limited by the binary purchase decision, where **M** is an arbitrary large quantity;
- Eq. (30) constrains solar conversion technologies to generate in proportion to the solar insolation and conversion efficiency;
- Eq. (31) ensures that the installed capacity of solar conversion technologies is limited to available space;

- Eq. (32) enforces energy balance in storage technologies by stating that in any time step the cumulative sum of net input over all prior time steps must be limited by storage maximum and minimum states of charge;
- Eqs. (33) and (34) place an upper limit in charging and discharging storage technologies;
- Eq. (35) sets the microgrid chiller conversion of electricity to cooling;
- Eq. (36) places an upper limit on how many hours each type of DER technology can generate during the year (possible user-defined restriction due to issues such as air quality);
- Eq. (37) determines how much heat can be recovered from CHP enabled DER technologies;
- Eqs. (38) and (39) ensure that electricity cannot be purchased and bought simultaneously in the same time step using a binary variable and where $\mathbf{M}$ is an arbitrary large quantity;
- Eq. (40) determines the annualized capital cost of DER investments;
- Eq. (41) limits the overall payback period of DER investments, considering both capital and operation costs, as well as utility cost offsets by comparison with a business as usual case;
- Eq. (42) prevents the use of recovered heat by end uses that cannot be satisfied by the particular DER technology;
- Eq. (43) guarantees that electrical power output from DER cannot be used for heating purposes;
- Eqs. (44) - (45) are boundary conditions that ensure the proper links between different technologies and the loads they can meet.

5. Case Study

The EV fleet Aggregator and stochastic implementation of DER-CAM introduced in this work has been tested by using detailed energy simulation loads of a large office building located in San Francisco, as described in the California End-Use Survey (CEUS) database. This database contains approximately 2700 detailed building loads of commercial buildings in California and has been used in previous work involving DER-CAM [25], [30], [31]. The large office building considered in this work has a peak electric load of 2.3 MW and a total electricity consumption of roughly 10.6 GWh, including electricity needs for cooling and refrigeration.

To create the DER-CAM models used in this work the energy loads contained in the CEUS database were processed to fit the 84 typical day data structure, and a large amount of additional data was collected, including average solar irradiation and ambient temperature for San Francisco, local utility tariffs and DER technology costs and performance coefficients.

The set of DER technologies considered includes internal combustion engines, micro- and gas-turbines, fuel cells, heat exchangers, absorption chillers, stationary electricity storage, photovoltaic panels, solar thermal panels, and electric vehicles.

Technology data

All costs and performance indicators of DER technologies considered in this work are listed in Table 1 and Table 2. The technology costs presented are forecasted for 2020, where it is expected that EVs will be widely available and V2G benefits within reach.

Table 1 - Discrete DER Technologies (2020)

		ICE		GT	MT		FC	
		S	M	-	S	M	S	M
capacity (kW)		60	250	1000	60	150	100	250
installation cost ($/kW)		2721	1482	1883	2116	1723	2382	1909
	w/HX	3580	2180	2580	2377	1936	2770	2220
maintenance cost ($/kWh)		0.02	0.01	0.01	0.02	0.02	0.03	0.03
electrical efficiency[1] (%)		29	30	22	25	26	36	36
HPR (if w/HX)		1.73	1.48	1.96	1.80	1.30	1.00	1.00
lifetime (years)		20	20	20	10	10	10	10

Notes: All technologies running on natural gas. S – small-sized model, M – medium-sized model, w/HX – with heat exchanger (using combined heat and power capabilities), HPR – heat-power ratio, ICE – internal combustion engine, GT – gas turbine, MT – microturbine, FC – fuel cell.

Table 2 - Continuous DER Technologies (2020)

	ES	AC	ST	PV
fixed costs ($)	295	93911	0	3851
variable cost ($/kW, or $/kWh when referring to storage)	200/150	685[2]	500	3237
maintenance cost ($/kWh)	0	1.88	0.5	0.25
lifetime (years)	5	20	15	20

Notes: ES – stationary energy storage, AC – Absorption Chiller, ST – solar thermal system, PV – photovoltaic.

The electricity tariff considered in this work is E-19 TOU (Time-of-use) tariff applied in the Pacific Gas & Electric service territory for buildings with electric peak loads over 500 kW [32]. It includes variable on-peak and off-peak energy costs for winter and summer months ranging from US$0.08/kWh in off-peak winter periods to US$0.16/kWh in on-peak summer periods, as well as seasonal power demand charges ranging from US$1.04/kW in mid-peak winter periods to US13.51$/kW in on-peak summer periods (Table 3).

[1] Higher heating value
[2] Absorption chiller costs are expressed in $/kW electric equivalent of an electric chiller

Table 3 – Electricity charges

(USD)	Power Demand Charges		Energy Charges	
	Winter	**Summer**	**Winter**	**Summer**
noncoincident	7.70	7.70	-	-
onpeak	0.00	13.51	0.156	-
mid-peak	1.04	3.04	0.105	0.093
offpeak	0.00	0.00	0.085	0.082

Note: noncoincident applies to the maximum power demand regardless of when it occurs
Summer: May to October; Winter: November to April
onpeak: summer week days from 12 to 18;
midpeak: summer week days from 8 to 12 and 18 to 21; winter week days from 8 to 21
offpeak: summer weekend days and week days from 00:00 to 08:00 and 21:00 to 24:00; winter weekend days and weekdays from 00:00 to 08:00 and 21:00 to 24:00

Storage parameters

In addition to the techno-economical parameters introduced above, the storage technologies used in this work were characterized by the additional performance coefficients shown in Table 4. These values represent state of the art forecasted values of both storage technologies considered [33–36].

Table 4 - Storage Parameters

	stationary electric storage	EV batteries
charging efficiency	0.90	0.90
discharging efficiency	0.90	0.90
decay per hour	0.001	0.001
maximum charge rate	0.30	0.45
maximum discharge rate	0.30	0.45
minimum state of charge	0.30	0.20

Note: all parameters are dimensionless

Finally, additional EV specific parameters used in this work are shown in Table 5, including average battery size, average electricity consumption for driving and battery replacement costs. The average battery size was obtained considering manufacturer information for Mitsubishi i-MiEV [37], Ford Focus Electric [38], BMW ActiveE [39], Nissan Leaf [40], Coda [41], and Chevrolet Volt [42]. Battery replacement costs were estimated based on battery degradation models and cost forecasts found in [43–45]. Fuel economy was calculated based on information from the U.S Department of Energy [46], [47]. The EV charging infrastructure investment costs at the microgrid for 2020 are forecasted assuming a decrease similar to that of batteries and based in data found in [48]. Available parking space is estimated specifically for the large office building used in this work.

Table 5 - EV Parameters

Average battery size (kWh)	23.75
Battery replacement cost in 2020 ($/kWh)	200
Hourly driving consumption (kWh)	4.2
Infrastructure investment cost per car ($)	1000
Total parking space at microgrid (m2)	16200
Parking space per car (m2)	15

Driving Schedules – Scenario Generation

The driving schedules used in this work were obtained from a 2009 US Commuting Survey [49]. This survey contains a detailed distribution of the departure time of employees commuting to work in the morning. In addition to this departure distribution, it was assumed that the average travel time would be 1 h, as this is the closest time period to the average one-way commuting trip allowed in the model. In addition, it was assumed that the average time spent at the microgrid site was 8 h and that the departure distribution on the way back home was the same as the departure distribution going to work. The resulting fleet departure distribution is illustrated in Figure 4.

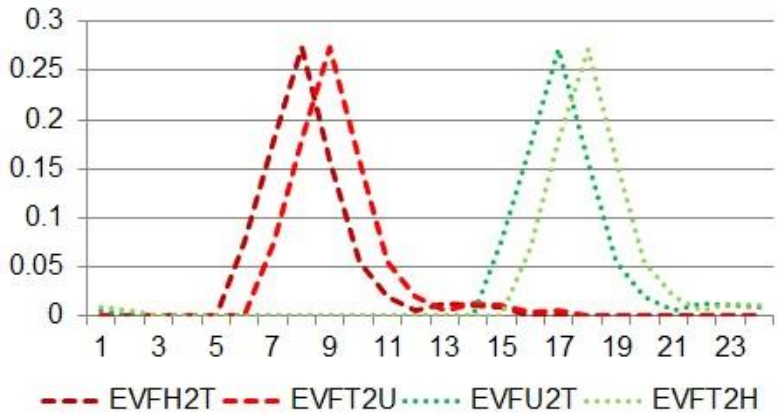

Figure 4 - Fleet Departure Distribution

In order to obtain the complete schedule of the fleet distribution in different states used in this work, an additional GAMS model was created to solve Eqs (1) - (4), considering the above departure assumptions. This problem has an indefinite solution due to the fact that only roughly 80% of the total fleet departure distribution is clearly defined over the day and the remaining 20% is scattered throughout the night. Combining these scattered departures and arrivals leads to an indefinite mathematical solution that can be thought of as instantaneous travels. To deal with this, three driving schedule scenarios were obtained using the aforementioned GAMS model and the objective of maximizing the number of cars at home (Scenario 1 – pessimistic), maximizing the number of cars at the microgrid (Scenario 3 – optimistic) and calculating an intermediate scenario between the latter (Scenario 2 – most likely). These driving schedule scenarios (Figure

5) were assumed to have equal probability of occurring and were used in the optimization runs discussed below.

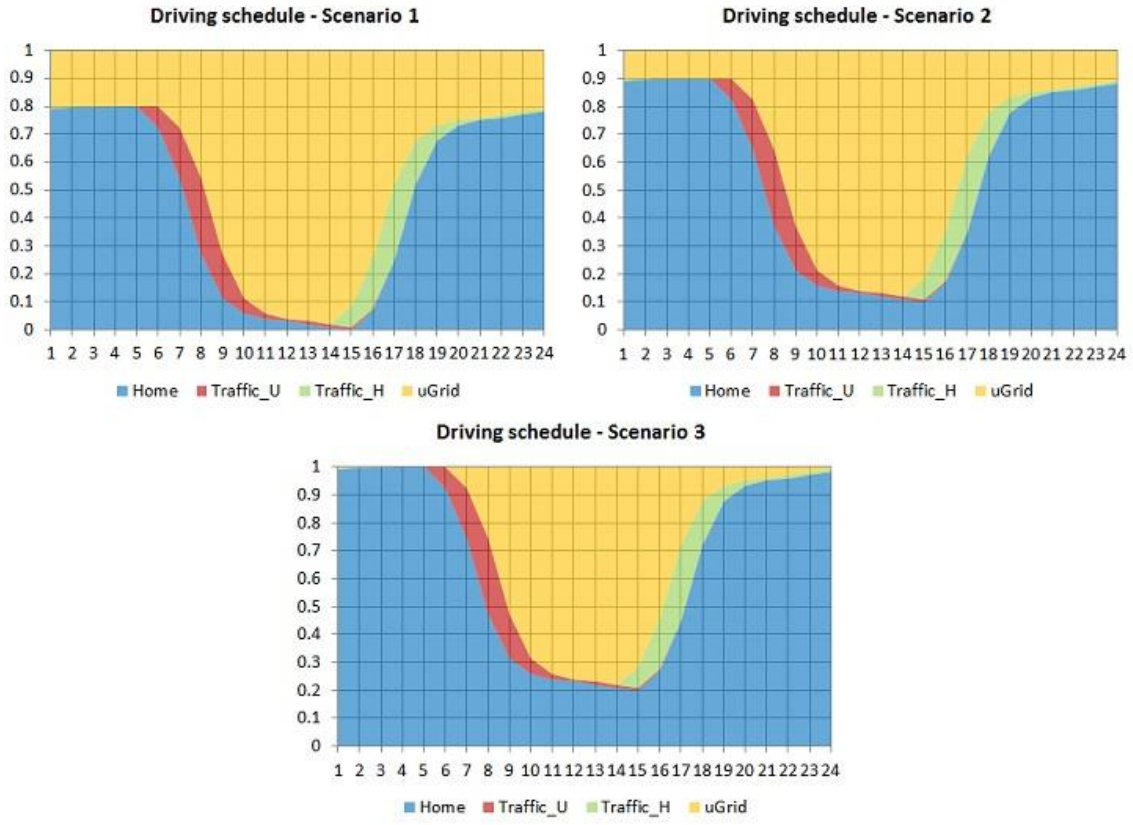

Figure 5 - Driving Schedule Scenarios

6. Optimization Runs

Model Options, Statistics and Performance

The model presented in this paper was run using 4 parallel CPU threads on a 256 GB RAM server running GAMS 23.0.2 and CPLEX 11.2.1. The solver options were set to a maximum execution time of 10 hours, a 5 million iteration limit and a 1% optimality gap. The number of equations and variables is shown in Table 6, according to the model options.

Table 6 – Problem Size

Model Options	Equations	Variables	Discrete Variables
No Investment in DER	210 926	159 035	22 186
Investment (Deterministic)	324 215	272 309	50 424
Investment (Stochastic)	915 041	759 189	127 032

Six different optimization runs were executed. They key options used in these runs are described in Table 7.

Table 7 - Key Model Options

REF.	Description	DER Investment	EV Investment	EV Schedule	Payback Period
BAU	Business as usual	N	N	-	
NOEVP5	Invest No EV	Y	N	-	5
EVS1P5	Allow EVs S1	Y	Y	S1	5
EVS2P5	Allow EVs S2	Y	Y	S2	5
EVS3P5	Allow EVs S3	Y	Y	S3	5
EVSTP5	Allow EVs Stoch.	Y	Y	S1, S2, S3	5
NOEVP12	Allow No EV	Y	N	-	12
EVS1P12	Allow EVs S1	Y	Y	S1	12
EVS2P12	Allow EVs S2	Y	Y	S2	12
EVS3P12	Allow EVs S3	Y	Y	S3	12
EVSTP12	Allow EVs Stoch.	Y	Y	S1, S2, S3	12

Key results and discussion

The computational results obtained are displayed in Table 8. With exception of run EVSTP12 all optimization runs reached the optimality gap well within the time limit. It must be noted that while the computational time results are considered acceptable, later versions of the CPLEX solver have proven to significantly improve the resolution time. However, at the time of execution the latest versions of CPLEX were not available on the server.

Table 8 - Computational statistics

Run	Total Energy Costs ($)	Computation Time (s)	Iterations	Optimality Gap
BAU	1 742 812	1.837	0	0.000%
NOEVP5	1 740 676	337.593	60730	0.000%
EVS1P5	1 588 059	779.691	114983	0.003%
EVS2P5	1 607 688	805.406	111697	0.083%
EVS3P5	1 623 344	1105.977	131812	0.068%
EVSTP5	1 607 547	10120.812	492815	0.091%
NOEVP12	1 608 008	482.574	87708	0.014%
EVS1P12	1 556 444	1322.835	188280	0.062%
EVS2P12	1 578 892	1215.935	167902	0.092%
EVS3P12	1 590 345	3002.327	194991	0.100%
EVSTP12	1 581 937	36065.341	671818	0.190%

The key investment results obtained in the optimization runs are shown in Table 9 and Table 10. These include total annual costs broken down to electric costs, natural gas costs, EV costs and non-EV DER costs, as well as CO_2 emissions estimations, and adopted capacity of all DER technologies selected by the model. Technologies

described in Table 1 and Table 2 that are not presented in these tables were included in the runs but not present in the results.

Table 9 - Investment Results. 5yr Payback as constraint.

Run	Total costs (k$)	DER costs[1] (k$)	Electric Utility costs (k$)		NG costs[3] (k$)	Total EV costs[4] (k$)	Total CO_2 (t CO_2)	Adopted capacity (kW \ kWh)				
			Total[2]	Power				PV	ST	ICE HX	ES	EV
BAU	1 743	-	1 506.1	439.5	236.7	-	6 444	-	-	-	-	-
NOEVP5	1 741	11.9	1 497.2	431.3	231.6	-	6 424	0	73	0	166	-
EVS1P5	1 588	87.3	786.4	199.7	359.3	355.1	6 239	58	0	250	0	25 650
EVS2P5	1 608	74.3	815.8	217.7	358.8	358.8	6 293	0	17	250	0	25 650
EVS3P5	1 623	74.2	922.4	263.3	359.0	267.8	6 216	0	15	250	0	18 242
EVSTP5	1 608	74.3	817.1	220.3	358.3	357.9	6 292	0	18	250	0	25 650

1- Includes annualized capital costs, and fixed and variable O&M costs. Does not include any EV related costs
2- Includes fixed costs, volumetric energy costs, and power demand costs
3- Includes NG costs for heating and for DER
4- Includes EV annualized charging station capital costs, battery degradation, and electricity usage costs

Table 10 - Investment Results. 12yr Payback as constraint.

Run	Total Costs (k$)	DER costs[1] (k$)	Electric Utility costs (k$)		NG costs[3] (k$)	Total EV costs[4] (k$)	Total CO_2 (t CO_2)	Adopted Capacity (kW \ kWh)			
			Total[2]	Power				PV	ICE HX	AC	EV
BAU	1 743	-	1 506.1	439.5	236.7	-	6 444	-	-	-	-
NOEVP12	1 608	477.8	619.9	162.6	510.2	-	4 620	1 128	750	143	-
EVS1P12	1 556	474.3	350.8	85.4	438.0	293.3	5 001	1 075	500	0	24 897
EVS2P12	1 579	482.4	419.9	108.7	442.4	234.1	4 853	1 143	500	63	20 695
EVS3P12	1 590	456.6	544.5	135.7	520.3	68.9	4 835	955	750	121	5 312
EVSTP12	1 582	439.2	472.2	102.8	516.4	154.1	4 896	970	750	120	12 506

1- Includes annualized capital costs, and fixed and variable O&M costs. Does not include any EV related costs
2- Includes fixed costs, volumetric energy costs, and power demand costs
3- Includes NG costs for heating and for DER
4- Includes EV charging stations, battery degradation, and electricity usage costs

By analyzing the investment results, a clear influence can be observed from the use of different maximum payback periods in microgrid DER investments. When considering a maximum payback of 12 years, the impact of introducing EVs is significantly lower on the total microgrid costs than when the maximum payback period is of only 5 years. In fact, by analyzing the results shown in Table 9, the presence of EVs introduces annual savings of approximately US$134 300 when using a maximum payback of 5 years (obtained calculating the difference in total energy costs in NOEVP5 with the average of EVS1P5, EVS2P5 and EVS3P5), whereas the same results is of only US$32 800 according to data in Table 10 – maximum payback of 12 years.

This result can be explained by the fact that when longer paybacks are allowed a significant capacity of both PV and ICEs coupled with heat exchangers are already part of the solution, which already have a significant impact on reducing total energy costs.

In this case, the contribution of EVs to reduce total costs is smaller, but it can be observed that in both cases EVs lead towards very similar solutions in terms of total costs. This can be confirmed by calculating the expected total costs in both cases: US$1 606 300 for 5 year paybacks and US$1 575 227 with 12 year payback periods.

Moreover, it must be noted that the investment solutions given by the model only consider the global payback period, and not the individual payback of each technology. While this may lead to solutions where some technologies individually have longer paybacks, it allows capturing economic benefits that otherwise could not be taken into account. This is one of the most relevant benefits of considering a holistic approach to the problem and it can be clearly observed in Table 9. When adopting a maximum payback of 5 years, adding the possibility of EV V2G services leads to the adoption of a 250 kW internal combustion engine coupled with heat exchangers, which is not part of the optimal solution when EVs are not allowed.

This suggests that when individually analyzing the ICE investment the optimal decision would be not to install, but adding EVs allows a greater use of the ICE which increases its economic performance, ultimately leading to its adoption. In fact, looking at the detailed scheduling obtained in run EVS2P5, the ICE capacity factor obtained is approximately 0.9 (Table 11).

Table 11 - ICE Month Capacity Factor in EVS2P5

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	AVG
0.99	0.99	0.98	0.95	0.89	0.85	0.8	0.81	0.79	0.87	0.97	0.99	0.91

This result can also be explained by the fact that in the optimal investment solution ICEs are used to partially charge the EVs, even in summer months where the capacity factor is below the average and the ICE is not used as often as in winter months (Figure 6). This additional use for the ICE has a two-sided effect on the economical results, due to the fact that it is driven by electricity consumption and coupled to heat exchangers for combined heat and power production. The higher capacity factor allows lower investment costs per kWh of electricity produced, as well as additional heat recovery that contributes to increase overall system economy and efficiency.

Shown in Figure 6 is the 7 day electric load profile for the month of August, where the dispatch found by the model is also illustrated. Here, utility purchase still represents the most important energy source, although both the ICE and EVs play a relevant role.

This dispatch illustrates the potential of EVs for V2G services, not only by allowing effective peak shaving by charging the cars at home and using the stored electricity at the microgrid (Figure 7), but also by enabling load shifting while cars are parked at the microgrid. This behavior can be observed when the cars parked at the microgrid are being charged in early morning hours.

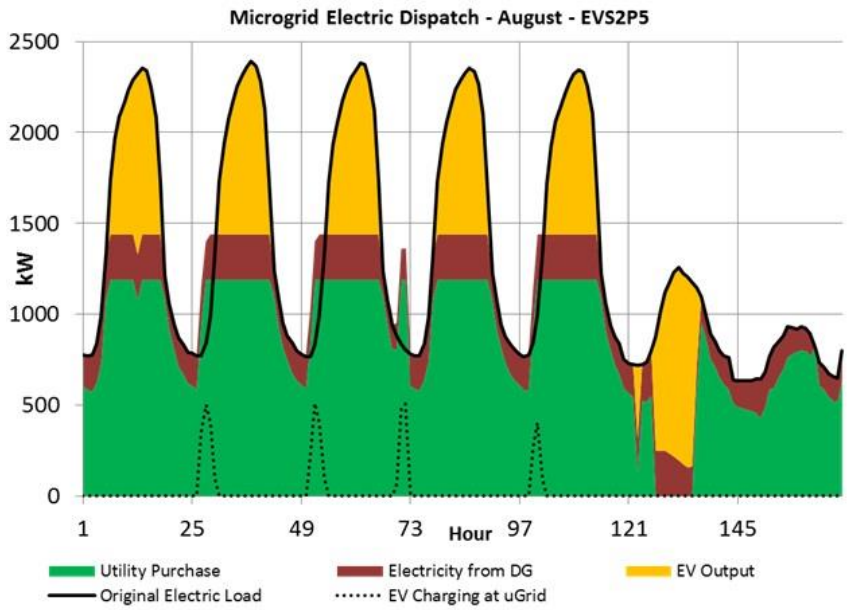

Figure 6 – Microgrid electric dispatch for August, EVS2P5

It should also be noted that the results in Figure 7 show a peak in EV home charging occurring at 5AM. This occurs as a result of the flat tariff considered during that period and the lower costs induced by this strategy as it minimizes losses from self-discharging. While this particular result does not have a significant impact on results, it would be desirable that in future developments this issue is addressed in order to achieve more realistic charging patterns.

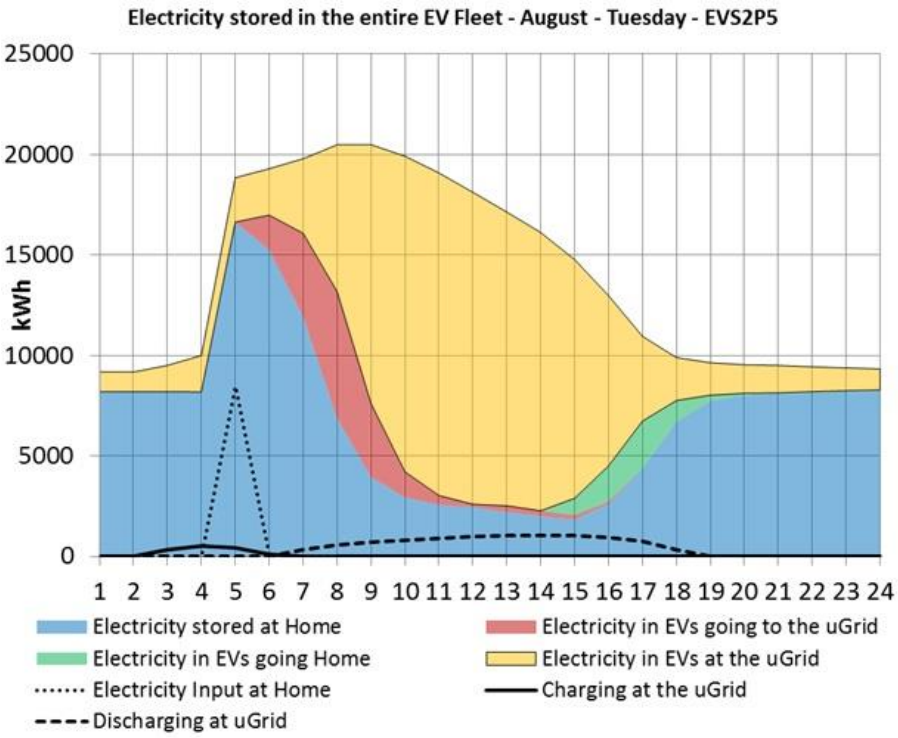

Figure 7 – Electricity stored in the entire EV fleet. Tuesday in August, EVS2P5

Analyzing how costs are distributed, it also becomes apparent that the presence of EVs has a very significant impact on the electric utility costs, both in energy and power costs. In fact, electricity cost reductions range from 12% in run EVS3P12 to 47% in run EVS1P5 and power demand charges are reduced from 17% to 54% in those respective runs. However, this is balanced by a significant overall cost with EVs, which justifies a further brake down of EV related costs (Table 12).

Table 12 – Detailed EV results

Run	Optimal Capacity (kWh)	Number of cars	Total EV costs (k$)	Charging station costs (k$)	Battery degradation costs (k$)	EV electricity costs (k$)
EVS1P5	25 650	1 080	355.1	146 370.6	162 826.6	45 918.6
EVS2P5	25 650	1 080	358.8	146 370.6	163 879.0	48 520.0
EVS3P5	18 242	768	267.8	104 095.5	125 528.3	38 186.3
EVSTP5	25 650	1 080	357.9	146 370.6	163 430.4	48 126.6
EVS1P12	24 897	1 048	293	142 075.9	118 012.2	33 200.7
EVS2P12	20 695	871	234.1	118 094.3	89 563.2	26 470.8
EVS3P12	5 312	223	68.9	30 309.9	29 573.8	8 983.0
EVSTP12	12 506	526	154.1	71 363.9	64 004.8	18 761.6

These results show that the charging station investment and EV battery replacement costs are the most significant share of costs, representing almost 90% of all EV related costs. Given that the prices used for both charging stations and EV battery replacements are being forecasted to 2020, it should be noted that the real impact of EVs on the adoption of other DER technologies may vary significantly depending on how these prices evolve. If prices become higher than the forecasted values it is expected that EVs no longer become part of cost-optimal solutions, whereas if market and technological developments leads to lower costs, it can be expected that the presence of EVs have a larger impact on the total microgrid costs.

It should be taken into consideration in the follow discussion that the number of cars found in Table 12 represent the optimal fleet size in the microgrid perspective, i.e., it represents the fleet size that, taking all costs into consideration and the assumption that EVs are widely available, would allow minimizing the total energy costs at the microgrid. Thus, variations in fleet sizes represent changes in cost-optimal decisions determined by the different settings considered.

Looking at the individual results obtained with different deterministic driving schedules it can be observed that the impact on total energy costs is relatively small, as well as the impact on technology choices, although not negligible. Depending on the driving schedule, there will be a different availability of EVs at the microgrid, which is reflected in results. Analyzing the 5 year payback optimization runs, we see that driving scenario S1, observed in run EVS1P5, leads to the adoption of a small amount of PV panels, and

no solar thermal panels, whereas scenarios where there is less availability of EVs (S2 and S3) lead to the adoption of no PV and to the adoption of solar thermal panels. This can be explained by the fact that the higher availability of EVs in the fleet distribution of driving scenario S1 allows a higher capacity factor of the ICE, and therefore an increased heat recovery that would otherwise be compensated by solar thermal panels.

In the 12 year payback runs, however, a different behavior is observed. In this case, the lower availability of EVs has a much more significant impact on the optimal number of EVs and on the adopted capacity of other DER technologies, although not on the technologies themselves, as in all cases large capacities of both PV and ICEs have been selected. It is observed that higher EV numbers lead to lower combined adoption of other DER, which is consistent with the strategy identified in Figure 7 where EVs are charged at home to meet part of the microgrid electricity demand. Furthermore, it is relevant to notice that the large discrete size of the ICE makes it a more suitable candidate for replacement than PV, which can be observed in the results obtained in driving scenarios S1 and S2.

Despite the changes in the optimal capacity of other DER technologies, the results obtained for individual scenarios lead to similar total microgrid cost results, which suggests that the uncertainty in the EV driving schedules is does not have a significant impact. This can be confirmed by the results obtained with the stochastic version of the model.

Namely, by analyzing the results in Table 9 and Table 10, the expected value of perfect information can be estimated by calculating by the numeric difference between the average of the total energy costs in the three individual scenarios and the total energy costs obtained in the stochastic model. This returns US$1184 in the 5 year payback runs and US$6710 in the 12 year payback runs, which is negligible given the precision used in the runs. These results are consistent the large capacity of EVs adopted in each of the runs, which is well over the electric peak demand in the large office building being considered. By taking this into account and considering the additional presence of ICEs and other DER, there is an indication that the flexibility of the optimal investment solutions in each run allows compensating the uncertainty in the driving schedules, which suggests a high level of reliability in the results obtained.

It must also be noted that while other sources of uncertainty could have a much higher impact on results, such as solar irradiation or utility prices, the focus of this work is on the EV driving schedules. Additionally, since the stochastic formulation of DER-CAM was implemented in order to allow modeling uncertainty in any parameter by doing simple adjustments in the code, other sources of uncertainty can be easily considered in future work.

Finally, the results obtained suggest that the introduction of EVs may lead to DER solutions that further contribute to reduce CO_2 emissions, although once again the

maximum payback period considered leads to different results, as CO_2 emissions are only reduced in results with 5 year paybacks.

This result can be explained by analyzing the grid CO_2 emissions, and particularly the data presented in Figure 8, where the average hourly deviations from seasonal average values are presented. Contrary to common perceptions, CO_2 emissions levels during the night may be higher than during daytime due to the energy mix, and therefore charging EVs during the night may add to total microgrid CO_2 emissions. In the results obtained, it should be pointed out that the heat recovery promoted in the ICE, and mode importantly, the adopted capacity of PV, are the main drivers for CO2 reductions, which explains the different results obtained for different paybacks.

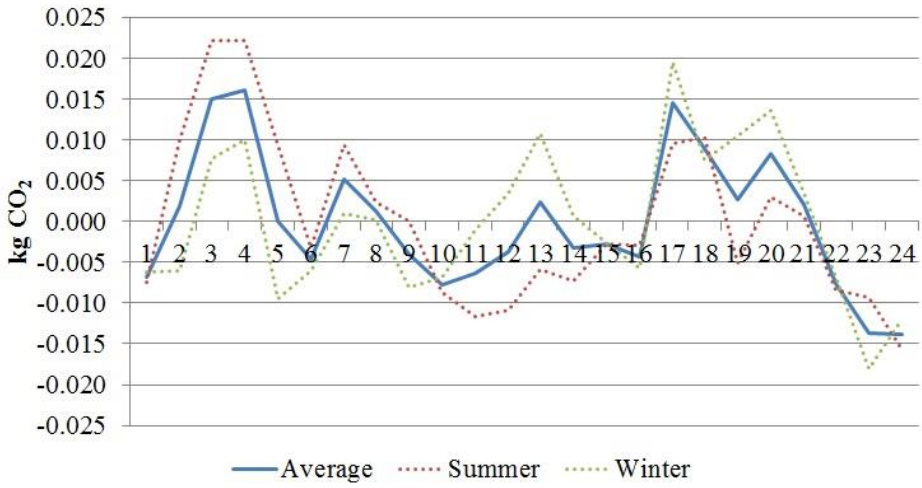

Figure 8 – Deviations from average seasonal grid CO_2 emission levels

7. Conclusions

This paper deals with the problem of optimally sizing and scheduling DER capacity at a given site, considering the effect of freely available electric vehicles and uncertainty in EV driving schedules. It adds to the current state of the art by introducing a novel EV fleet aggregator model and developing a stochastic formulation of DER-CAM, a widely used model in DER sizing and scheduling problems. The aggregator model presented in this paper is based on a time-dependent fleet distribution that considers four different fleet states and transitions between them.

The model is used to analyze the case study of a large office building located in San Francisco, and real driving departure data are used to analyze the impact of EV driving schedule uncertainty in the DER investment decision.

Results suggest that the presence of an EV fleet can have a relevant impact on total energy costs, provided the payback periods are relatively small. In this case, results suggest that EVs foster the adoption of additional DER technologies, which combined

with EVs allow significant energy savings coupled with CO_2 reductions, even considering a purely economic objective function.

In higher payback scenarios, however, EVs show a lower impact on the total energy costs and DER investment decisions, as other technologies gain a higher weight.

Results also suggest that considering uncertainty in EV driving schedules has little impact on total energy costs, which can result from the flexibility provided both by the large amount of EV adoption and the additional installation of local generation, although the optimal adopted capacity varies depending on the EV availability. This result is obtained by comparing total costs obtained for three different driving scenarios and confirmed by calculating the expected value of perfect information and the value of the stochastic solution using the results obtained with the stochastic model, thus indicating that EV adoption should be considered in DER investment decisions.

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